# MSLesSeg 2024 Challenge - MSUniCaTeam's Technical Report

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The approach proposed by MSUniCaTeam is based on an Ensemble of different Deep Learning models. The networks used to create the ensemble are Swin-UNETR [1], UNETR [2] and SegResNet [3]. To improve training performance, the following preprocessing and augmentation were used:

- **Contrast Merging**: since each volume was provided in three different contrasts (FLAIR, T1-weighted, and T2-weighted), we overlapped the individual contrasts to create a new set of images with three channels;
- **Random Cropping**: a random volume crop, with a specific ROI size of $128 \times 128 \times 128$. The choice of this dimension comes from several trials done during the training phase where the ROI sizes of 32, 64, 96, and 128 were tested. Dimension 128 was found the one that obtained the best results in the validation set.
- **Intensity Normalization**: for each image, the intensity was normalized, bringing intensity values with mean 0 and standard deviation 1. Only voxels other than 0 were considered. Intensity normalization was applied individually for each image channel.

These steps increase data diversity and prepare it for robust model training.

The experiments were performed on a workstation with an Intel(R) Core(TM) i5-13500 @ 2.50GHz CPU, 32 GB of RAM, and an NVIDIA RTX 4060 Ti GPU with 16GB of VRAM.

Each model was trained for 600 epochs with a batch size of 2, for 25200 iterations per model. The total time to train the model was about 7 hours and 38 minutes to train SegResNet, 9 hours and 11 minutes to train UNETR and 120 hours and 44 minutes to train Swin-UNETR. Please note that Swin-UNETR did not improve the validation set after epoch 80, taking about 19 hours to reach it. Apart from the batch size of 2, 8 workers were also used. In this way, it was possible to load 16 images into VRAM at a time, thus reducing the training time.

The validation was done every 2 epochs, calculating the Dice metric on the validation set. The model was saved when the previous best Dice metric was exceeded.

Each network shares the following structure:

- number of spatial dimensions: 3 (X, Y, Z);
- number of input channels: 3 (FLAIR, T1, T2);
- number of output channels: 2 (Lesion, Background);
- dropout probability: 0.4.

The update of the weights of each model was done according to DiceLoss, which is calculated as follows:

$$DiceLoss(y, y_{pred}) = 1 - \frac{2 * y * y_{pred} + 1}{y + y_{pred} + 1}$$

Once each model had been trained, the predictions were produced individually and combined by computing a weighted average.

The weights to compute the average are the DiceMetric values obtained in the validation set by each model.

These values were then provided as input to a Softmax function, which returned a probability distribution between 0 and 1, the sum of which makes 1. This made it possible to reward the best-performing models while still obtaining useful information from the other models.

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## References

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